ALGORITHMIC AND NON ALGORITHMIC TRADING ACTIVITY IN THE BSE USING LIMIT ORDER BOOK OF SELECT STOCKS

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by

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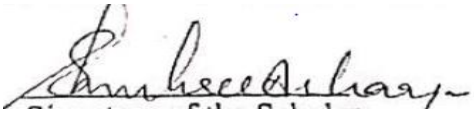

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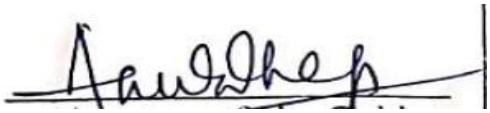

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ABSTRACT

With the existence of a heterogeneous market compounded by asymmetric information, Algorithmic traders are playing a dominant role in order placement , order modification and order execution. This study aims to understand the trading activity of both the market participants. The study uses the Limit Order Book data from Bombay Stock Exchange. The Order Added, Order Updated and Order Deleted along with the Bid Ask Quotes are considered for measurement for the selected 9 stocks. Based on the Limit Orders it is observed that there is a statistically significant difference in the trading behavior of Algorithmic and Non-Algorithmic traders based on Market Session and Market Capitalization. The market Making ability of the Algorithmic traders was examined using Order-to trade Ratio and it is observed that large number of Orders are not executed indicating that there is no significant Market Making happening. The Algorithmic traders possess an edge over the Non-Algorithmic traders in Order Modification resulting in dominance in the Stock market.

Key words: Algorithmic trading, Non-Algorithmic Trading, Market Session, Market Capitalization, Market Making

INTRODUCTION

The emergence of prominent stock exchanges across the World confirm that stock exchanges are a central financial institution in any capital market. An active stock market helps in the economic development of a Nation. Financial markets around the world play a pivotal role in ensuring perpetual flow of capital into productive sectors. There is sufficient literature available that appreciates the role played by financial system in long term growth of an economy. Several research have been undertaken with an objective to approve or disapprove the above notion. And thus it can be concluded that a stock market plays a significant contribution in economic development.

According to the data compiled from the World Federation of Stock Exchanges in Fig 1.1 for the month of December 2020, NYSE is the stock exchange with highest Equity market capitalization (EMC)* followed by NASDAQ. The National Stock Exchange of India (NSE) is the tenth Stock exchange with highest EMC.

Fig.1.1 Equity Market Capitalization of Stock Exchanges globally

Source: www.world-exchanges.org

Fig1.2 represents the timeline of Total Value of Stocks Traded** around the world. With 1.747 Trillion USD in the year 1984, the value of stocks traded stands at 84.156 Trillion USD (2019) according to the database of World Federation of exchanges.

*EMC is the total outstanding shares of all the listed companies multiplied by current market price of each listed share

**Total Value of stocks traded is the total number of shares traded multiplied by price at a point of time

Fig.1.2 Total value of stocks traded globally from 1975-2020

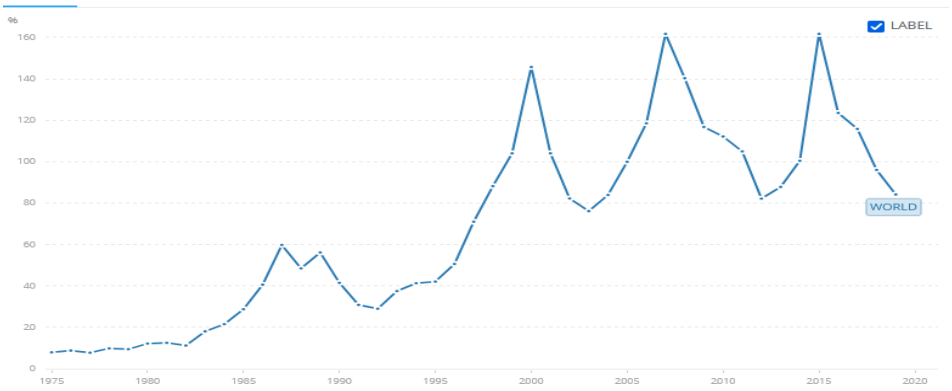


Image Source: World Bank Data

The above figures are indicative of Stock Exchanges' holding an important position in the Financial system.

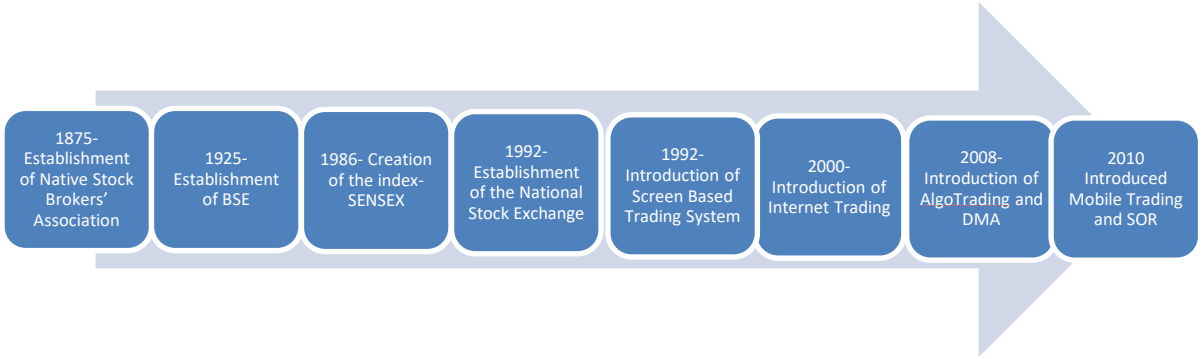
Technology and stock market in India

With the advent of technology stock markets started evolving. There is sufficient academic literature asserting the role of technology in transforming the Capital markets especially of developing countries.

The progress of the Stock exchanges in India particularly the BSE and NSE can be attributed to the adoption of technology. The trading activity in securities market intensified with the establishment of the National Stock Exchange of India Ltd in the year 1992. The sophisticated technology introduced by the establishment of NSE revolutionized and modernized the trading scenario in India.

Below is the time line of technological advancements in the history of stock trading in India.

Fig 1.3 Time Line of technological developments in Indian market


1875- Establishment of Native Stock Brokers' Association
1925- Establishment of BSE
1986- Creation of the index- SENSEX
1992- Establishment of the National Stock Exchange
1992- Introduction of Screen Based Trading System
2000- Introduction of Internet Trading
2008- Introduction of AlgoTrading and DMA
2010 Introduced Mobile Trading and SOR

Along with the above introductions another landmark in 2008 was the decision by Securities Exchange Board of India (SEBI) to permit Algorithmic Trading in BSE and NSE. The developments especially the introduction of Algorithmic Trading and Online trading was a shot in the arm for stock market development. Rapid improvement in technological sphere gave access to faster dissemination of market information, speedier execution of trading, creation and execution of various trading strategies. Computer- based trading gave rise to a new set of traders known as Algo-traders and High-Frequency Traders who have now become the most predominant stock market players.

Algorithmic trading

Algorithmic Trading, hereafter called as AlgoTrade or AT is a method of trading which uses computer programmes to enter/exit trades. The computer programmes here mean set of instructions. The algorithms are designed to identify signal based on metrics like time, price, volume. Several authors have tried to define the term AT and all the definitions have the common thread which is the use of computer algorithms inorder to place order. Hendeshott who is one of the pioneering researchers in the area of AT quotes Algorithmic trading is the use of algorithms in order to make trading decisions (Hendershott, 2011). The algorithms deploy

intricate and often complex mathematical models to identify and execute orders. It is argued that Algotrading minimizes cost and improves market efficiency and market liquidity.

The most frequently cited advantage of using Algorithms to execute orders is to harness speed and frequency which cannot be matched by human traders.

Algorithmic trading in India

Algorithmic Trading in India was embraced by India in 2008. The Indian Securities Market Regulator SEBI permitted NSE and BSE to extend Algorithmic Trading facilities to their members and further issued guidelines to regulate AlgoTrading activity in India. As per SEBI Circular No. CIR/MRD/DP/09/2012 dated March 30, 2012, Algorithmic Trading has been defined as "any order that is generated using automated execution logic." AlgoTrading in India further received a fillip through the introduction of Colocation facility*.

Table 1.2 shows the Algorithmic Trading activity Y-o-Y. The data has been extracted from the SEBI Handbook of Statistics-2020. The algorithmic activity is the aggregate of BSE & NSE's Cash and Equity Derivative segment.

Table 1.1 Algorithmic Trading Activity Y-o-Y

Period	NSE		BSE	
	Cash (in percentage)	Equity Derivative (in percentage)	Cash (in percentage)	Equity Derivative (in percentage)
2010-11	13.94	5.5	-	-
2011-12	16.90	4.9	-	-
2012-13	17.60	5.0	-	-
2013-14	18.11	5.4	-	-
2014-15	16.13	3.7	16.5	16.0
2015-16	17.72	4.1	11.2	3.9
2016-17	17.08	4.1	11.8	7.5
2017-18	15.34	3.7	8.8	41.3
2018-19	16.26	4.4	8.6	0.9
2019-20	15.32	5.0	10.0	4.8

2020-21$	11.67	3.6	6.8	14.5

Source: SEBI Handbook of Statistics—2020

$ Data of 2020-21 is till

Algorithmic Trading activity based on Limit Order Book data

The Algorithmic orders contribute about 95% of the orders generated in BSE and NSE. The below table indicates the total number of orders (TO_t) received per second for a time frame of 6 seconds for selected 30 stocks in BSE Limit Order Book. The orders are an aggregation of Total number of new orders (A), Total number of modified orders (U) and Total number of deleted orders (D) of each second 't'.

$$TO_t = \sum(A_t, U_t, D_t)_t$$

The below data shows the order inflow of Algorithmic based and Non-Algorithmic based orders in a span of 6 seconds; commencing from 9 hours 15 minute 3 seconds (09:15:03)IST. Each second's total orders are based on aggregation of order entry at Micro second time granularity.

Table 1.2 Details of 6 seconds Total Limit Orders

Time in seconds (IST)	**9.15.03**	**9.15.04**	**9.15.05**	**9.15.06**	**9.15.07**	**9.15.08**
Algo Orders	1133	1082	893	760	702	1024
Non- Algo Orders	47	58	88	61	43	54

Source: Computation made with BSE's LOB data obtained from BSE

From the above table it can be inferred that the Limit Order Book comprises of 2 types of market participants namely Algorithmic and Non Algorithmic Traders. Almost 95% of the orders that are placed in the Limit Order Book are from the Algorithmic Traders. This reveals the power of Algorithmic Traders in rapid placement, modification and cancellation of orders. The order intensity has been calculated as below

Algo Order Intensity= $\sum(A_t, U_t, D_t)_A \div \sum(A_t, U_t, D_t)_{A\ \&N}$

The denominator represents the total of A, U and D orders placed by Algo and Non Algo

PROBLEM STATEMENT

With the emergence of Algorithms used to extensively automate the process starting from market research to order execution to order monitoring has created a niche for few participants known as Algotraders. Those participants who do not use algorithms form another segment of the market known as Non-Algotraders or human traders. With such a differentiated market of advanced technology compounded with asymmetric flow of information can impact the market microstructure. It is to be ascertained if the Algotraders and Non Algo traders continue to show any varied trading behavior and if Algotraders reveal any different market interaction.

NEED FOR STUDY

Algorithmic Trading commanding a major share of almost 95% daily trading activity in the stock market has created opportunities and benefits as well as concerns. Albeit benefits and opportunities are sufficiently addressed by the research community, the concerns that have emerged are not sufficiently addressed. Two such questions which this research attempts to explore are ; the similarities (and/or) dissimilarities in trading behavior of the two market participants (AT & NAT) especially in the backdrop of an asymmetric heterogeneous market. The second concern is the relevancy and redundancy of Human Traders in the future days of the Stock market. There are fragmented opinion about the relevance of Human traders, the academic literature is thin regarding the trading behavior of AT and NAT.

This study aims to explore the interaction between the Algorithmic Traders and Non-Algorithmic Traders in the Capital market. For the purpose of this study we intend to examine trading activity in general and the convergence and divergence of Algorithmic and Non-algorithmic traders

RESEARCH QUESTIONS

Research questions articulate the purpose of the study and also pave way to the appropriate methodology to be used in order to achieve the overarching purpose of the study. This study aims to understand the similarities and dissimilarities of Algorithmic and Non Algorithmic Traders and the consequent changes which are likely to follow with the increase in the presence of Algorithmic activity in the Indian bourses. Following are the research questions which define the overall scope of this study.

RQ1. What are the distinct features of Algorithmic Trading/Trader?

RQ2. How has Algorithmic Trading activity impacted Stock market?

RQ3. Do the Algorithmic and Non-Algorithmic market participant show significant difference in trading behavior?

RQ4. What are the emerging concerns consequential to the dominant presence of Algorithmic trading in Indian Bourses especially with a trading behavior significantly distinct from Non Algorithmic-traders.

DISCUSSION OF LITERATURE REVIEW

A thematic review of literature was conducted in order to explore the existing knowledge under study. The themes have been constructed in alignment with the research questions. Following were the themes on which Literature Review was undertaken.

- Studies on Algorithmic Trading and High Frequency trading
- Studies on impact of Algorithmic Trading on Liquidity, Volatility, Price Discovery
- Studies on market making
- Studies on Trading behavior of Non Algorithmic traders
- Studies on interaction between System and Human Traders

Based on the literature following are the brief review and research gap associated with the themes

Algorithmic Trading is prevalent for more than fifteen years and despite becoming one of the most popular trading mode, the academic research in this area is largely in the developed markets. One of the reason for a tepid research approach can be attributed to non-availability of public data. The dataset required to perform most of the quantitative research in Algorithmic Trading necessitates the availability of Tick-By-Tick Data (TBT) or Order data. A TBT dataset is most often a product and proprietary to a Stock exchange and not available publicly. Also a TBT data set requires high computational capability owing to its size which requires a sophisticated infrastructure to process the Data.

Theme 1: Algorithmic trading and features

Once upon a time stock or share trading used to happen through open outcry system where traders dealt in trading by being in the trading pit physically. “The modern trading floor resembles a library where most of the trading is done electronically” (Kissell, 2021, p.1). With the introduction of algorithmic trading, the use of technology in trading heightened. Research by Hendershott et al.,(2011); Hendershott & Riordan (2013) brings out the meaning of algorithmic trading. This study considers the definition as given by SEBI in its Circular No.

CIR/MRD/DP/09/2012 dated March 30, 2012, Algorithmic Trading has been defined as "any order that is generated using automated execution logic" (SEBI, 2012). (Gsell, 2009) in his research investigated the adoption of algorithmic trading as an advanced technological disruption, examined the willingness of especially buy-side institutions in adopting this technology. He uses a modified TAM , TRA model . The research concludes that adopting algorithmic trading gives a competitive advantage to the users over the non-users and also it exceeds the expected performance. Although the size of the respondents for this research was less, it paves the way to understand how this technology has been accepted. Algorithmic trading uses various algorithms for achieving a designated purpose like VWAP algorithm, TWAP algorithm, MOC and implementation shortfall to name a few Gsell (2008), Sharma (2012). Through the literature one feature of algorithmic trading is the ability to place and execute orders at great speed. (Scholtus et al.,2014) investigated the importance of speed and low latency to obtain expected trade returns. Using the order and trade data of highly liquid stocks the researchers conclude that a delay in 300 milliseconds diminishes the trade returns by 3.08% especially when there is a macro economic related news. (Gsell,2008) suggests ATs have the capacity to process large volume of trade at very high speed. But the above research leaves room to observe the interaction between one algorithm to the other and with no algorithm. The interaction and response to news in milliseconds has a huge impact on market.

Theme 2: High Frequency Trading (HFT)

The ability of low latency and harnessing speed leads to the sub category of algorithmic trading namely High Frequency Trading popularly known as HFT. HFT is a subset of algorithmic trading. Brogaard (2010); Zhang, (2010); Brogaard et al.(2014); have identified HFT using various proxies like frequencies of the number of orders, time stamp of various orders, repeated number of quantity of orders at various price quotes. They all identify HFT as a subset of algorithmic trading because HFT requires algorithms. (Zhang, 2010, pg. 1) defines HFT as "fully automated trading strategies with very high trading volume and extremely short holding periods ranging from milliseconds to minutes and possibly hours". Brogaard (2010) examined the impact of HFT on equity market. According to him HFT based trading is more dominant than human based trading. HFTs trade in large volume stocks, and they reduce trading as volatility increases. This is contradicting other studies which say algorithmic activity does not change even when

volatility increases. The advantage of Brogaard (2010) study is the data set which is unique containing unique codes, market volume, capitalization, inside quotes and identification of HFT and non-HFT. He concludes that HFTs add to price discovery process and they trade at milliseconds time speed. The working paper concludes that HFTs do not affect the non-HFTs. On the other hand , Hendershott & Riordan (2012) examined the role of HFT on price discovery by taking order data and conclude that HFTs contribute sometimes to market efficiency and liquidity. But all these literature do not address the other segment of participants which is the NAT or non HFTs. These HFTs and other ATs do not contribute anything to the fundamental value of a stock. Since the HFT-AT traders do not trade nor hold positions, does efficient market have any relevance Zhang (2010).

Theme 3: Algorithmic trading and its impact

The above studies lead several researchers to understand the impact of AT on various dimensions of the stock market namely; liquidity, volatility, price discovery and market efficiency. Liquidity is very vital for a thriving market. Whether in a Quote driven market or in an Order driven market, liquidity is crucial for the functioning of the trading system. In this regard since Algorithmic traders possess the potential to quickly adjust their trading behavior to changes in the information, they have the ability to alter the Liquidity conditions of the market at a given point of time. Therefore, many researchers have tried to explore the impact of Algorithmic trading and also High Frequency trading on stock market liquidity. Hendershott, Jones & Menkveld (2011) are the authors whose research work in the area of Impact studies of AT can be considered as a pioneering work. The authors attempt to examine the impact of AT on stock market liquidity. The results show that a unit change in AT leads to narrowing of 0.53 points in spread suggesting that AT activity leads to increase in liquidity. In the subsequent research Hendershott and Riordian (2013) examine the role of Algorithmic Traders (AT) in supplying and demanding liquidity. Though this research is on the similar lines of study by Hendershott (2011); it assumes the perspective of ATs as liquidity suppliers and demanders. In this study the authors consider the 30 Large Market capitalizations stocks of the Deutsche Bourse- DAX Index. The study says that AT trades are almost 57% with respect to smaller trade volume (500-1000 shares).The study concludes that ATs and NATs both trade when spread is narrow but ATs are more aggressive. However it could not gauge if the NATs are dependent on ATs or vice versa in

market monitoring. It can be assumed that ATs are dominating than NATs. Also since the DAX had initiated a fee-rebate mechanism in the early introduction of algorithmic trading, it incentivized the ATs to trade more.

Stock market liquidity has a very significant bearing on the volatility. Therefore, it is imperative to understand if Algorithmic Trading activity has any favorable or unfavorable effect on Stock market volatility.

Several authors have attempted to understand the impact of Algorithmic Trading on Stock Market Volatility. Groth (2011) opines that the electronic revolution has brought about a surge in the Volumes of trade. But the research in examining volatility is not extensive as on liquidity. The author further investigates the market sidedness of ATs and Human Traders i.e. to which side (BUY/SELL) of the Order Book are the orders accumulating. Their research concludes that both type of participants exhibit similar behavior of market sidedness. The research concludes that AT does not contribute to market volatility and instead it is the NAT who may be contributing. The impact of HFT on stock market volatility and price discovery by Brogaard (2010); Zhang (2010); Hendershott & Riordian (2012) is discussed in the above discussion. Several researchers identify the impact on stock market, none of the research address the AT activity behavior on the NAT. Although AT has minimized volatility, improved liquidity it does not address the impact on NAT. Owing to high speed and low latency, ATs are able to garner several advantage, but it does not address if the trading behavior of NAT has changed accordingly or has AT eroded a level playing field?

Theme 4: Market making in an quote driven and order driven market

The existence and interaction of Buyers and Sellers for a commodity constitutes the fundamental of a market. These participants undertake the responsibility of providing continuous buy or sell tradability and therefore make a market.

Market makers in a stock exchange are an important infrastructure who are committed to provide liquidity to a stock. O.Hara.M (1986) refers a market maker as a dealer who assumes dual position of a buyer as well as a seller. (Shen & Starr, 2002) in their research article identify the predominant function of a market maker as a Liquidity provider. The market maker performs the function of an intermediary by buying from and selling to respective counter parties in a stock

market. It can be inferred that a Market Maker transacts on both sides of the market; Buy side and the sell side of the market and convey their intention in the form of QUOTE.

(Shen & Starr, 2002) in their report *on Market making and Proprietary Trading* describe Market maker's role in the bond market. Although the dynamics of a stock market and bond market vary, the similarity is in terms of trading and in the need for liquidity i.e prevalence of buyers and sellers to facilitate transaction. They identify a market maker as liquidity provider and also who absorbs market volatility shocks. With the introduction of Electronic trading in most of the developed stock exchanges, the traditional system of trading through Market Makers is waning. The ability of the market to display the BID/ASK prices of every trader created an alternative trading mechanism known as "Order-driven market". (Matsunaga & Kita, n.d.,) describe an Order driven market as in which price of a security are arrived at by matching the buy and sell orders offered by traders. The emphasis in an order-driven market is that there is no one party known as specialist. Such a system displays the Buy or Sell price of every trader. Market making activity especially by ATs in an order driven market is unexplored. The possibility of this might be that market makers do not exist in an order-driven market. But ATs use market making algorithms to scalp the Spread (The difference between the ask price and the bid price)

Theme 5: Non algorithmic trader (NAT) and their behavior

The theoretical background to understand the behavior of a human investor emerges with the study of 'Disposition effect' by Shefrin and Statman (Shefrin & Statman, 1985). Their pioneering work paved way to understanding the psychological dimension of an investor. The seminal work of Daniel Kahneman and Amos Tversky on 'Prospect theory' (Kahneman & Tversky, 1979) contributed in understanding the behavioral pattern of a human investor while taking a financial decision. Some of these theories contradicted that human investor behaves rationally while taking a financial decision. Through the extant literature available the theoretical framework about the typical behavior of a human investor and or a human trader has been explained. This framework is vital in this study in order to understand the atypical behavior and bias that influence the decisions of a human trader. (Barber & Odean, 2011) (Zahera and Bansal, 2018) based on their study, describe several bias observed in a human while making investment decision.

From the research it is evident that Algorithmic Traders possess a distinct character when compared to a Human Trader (Non Algorithmic Trader) especially in terms of speed of execution, ability to influence market and also possess the ability of market making. On the other side there is sufficient literature that surmises the typical trading behavior of a human trader.

Theme 6: Studies on interaction between System and Human Traders

(DeLuca et al.,2011) in their research raise the question of utilizing human traders to execute trades may soon become defunct as algorithms are better equipped to execute orders at faster rate and also a cheaper rate. Domowitz and Yegerman confirm that Algorithmic Trading is cost effective. Domowitz & Yegerman (2005)

(Gomber, 2009) in his research aims to understand the distinction between human traders and Algorithmic Traders in terms of order placement. The aim of the authors is to understand the order placement strategy by Algorithms and how different it is from the human traders' order placement. They conclude that there is a statistically significant difference between AT and Humans in terms of different order types and placing the order.

(MacKenzie, 2019) in his research lucidly explains how an algorithm interacts with another algorithm indirectly through the Stock exchange server's Electronic Limit Order Book. Since the algorithms are capable of entering orders in the LOB on Buy side as well as the Sell side which is later processed by the Stock exchange's Matching Engine; the algorithms are either 'Liquidity –taking' i.e aggressive where the algorithm places a SELL order resulting in removal of existing orders or the algorithms can be 'Liquidity providers' where orders are posted in the book that await execution. The author asserts that there is a significant difference between an Algorithm and Human trading behavior where in it is the human trader's strategic thinking that distinguishes them. Also the ability of the Algorithmic Trader to alter BID/ASK quotes and assuming a role of a market maker in an Order-driven market leaves scope for further exploring.

Research gaps and lack of study

The extant literature on algorithmic trading and HFT describe the increasing presence of algorithmic trading and also the way in which the order book and trade books of the stock

exchange are changing. The impact studies measure the impact of AT on market microstructures. The ATs with their speed, computing ability and rapid execution possess the edge over other market participants. Although both ATs and NATs have a common objective of making profits, their trading behavior has not been examined. There is very less literature that examine the interaction between AT and NAT. Most of the literature do not mention about the impact AT has on NAT. Following research gaps have been identified:

- What is the order placement pattern of ATs and NATs and is there a significant difference especially in an order driven market like the Indian stock exchange?
- The research concludes that there is impact of Algorithmic Trading on Liquidity where by the Algo Traders (AT) is able to rapidly place, modify and delete orders. However this may not be in favor of Non-algorithmic Traders (NAT) since the "apparent" visible liquidity may not be prevalent in the Order Book throughout. Also the NAT may not be able to adjust their trading behavior to rapidly changing liquidity positions.
- Although ATs improve liquidity in the markets, is this liquidity uniform for all stocks or is the liquidity only for well traded- high volume stocks?
- Since ATs have the advantage in terms of speed, is there a significant difference in AT and NAT activity in a trading day.i.e does the AT and NAT activity vary based on session timings?
- In a quote driven market, market makers play a significant role by standing to BUY or SELL depending on the direction. With the speed which ATs possess they play the role of a market maker. But in a quote driven market it requires to be explored if market making is visible especially by ATs.
- Since the Indian stock exchanges are order driven markets, does the orders placed and deleted by AT and NAT have any significance?

RESEARCH METHODS

Research design and paradigm

This study is based on the positivist paradigm of research. Positivism as a paradigm assumes that there exists an "apprehendable reality" and the investigator and the object of investigation are independent. (Guba & Lincoln, 1994, p. 109) The positivist paradigm relies on formulation of hypothesis and gathering empirical evidence to analyze the argument and either rejected or failing to reject the argument. (Cohen et al., 2007, p. xx) Since the problem under study emerges from an argument or a context that the trading behavior of Algorithmic and Non Algorithmic Traders vary; this argument requires testing an existing theory.

Each research question is a proposition i.e which is in the manner of a hypothesis that aims to establish or refute a relationship of the variables with the phenomenon. Since it is assumed in this study through literature review that there is a significant dissimilarity in the order placement (Orders added and deleted) behavior as well as the capacity in using computational power by Algorithmic and Non algorithmic traders, this study aims to test the argument by measuring relevant variables. Therefore a deductive form of reasoning is adopted for this study. Since the study requires analyzing numerical data, a quantitative research method is adopted.

Purpose of the study

The study is to examine the trading exploring dissimilarities in trading behavior of Algorithmic and Non-Algorithmic market participants based on selected variables and the consequent changes it can bring forth in the nature and structure of the market participants due to the increasing presence of Algorithmic Traders.

Data and Methodology

For the purpose of this study we intend to examine trading activity in general and the convergence and divergence of Algorithmic and Non-algorithmic traders with the historical data of Bombay Stock Exchange's Limit Order Book.

The Stock exchanges in India are an ORDER-DRIVEN market place. i.e.all the buyers and sellers can see the Orders placed by another market participant. Every order for a stock entering the server of the Stock exchange is time stamped and is given a unique Order ID. This order can be to purchase (or sell) Security X at Price P and Quantity T. If the Order is to BUY Stock X then it is termed as BID and if the Order is to SELL Stock X then it is an ASK. It is to be noted that the ASK quote (price) of a stock is always higher than the BUY quote:

$$\textbf{Px ASK} > \textbf{Px BUY}$$

Here **Px ASK** refers to price at which a trader is willing to SELL Stock X and **Px BUY** refers to price at which a trader is willing to BUY Stock X.

A Limit Order is an order that requires the trader to specify the price at which he/she is willing to BUY or SELL a stock at subjective to their trade position. A Limit Order Book (LOB) consists of all the Limit Order Trades placed by a trader at a given time. A trader may place an order to BUY and/or place an order to SELL. Those orders which are waiting to be matched by the Stock Exchange's engine rests in the LOB. Below is an image of a LOB.

Fig.1.4 Sample of a Limit Order Book

Buy			Sell		
Sr.No.	Quantity	Price	Quantity	Price	Sr. No.
1	1000	3.50	2000	4.00	5
2	1000	3.40	1000	4.05	6
3	2000	3.40	500	4.20	7
4	1000	3.30	100	4.25	8

Source: NSE website

Order No1 indicates an order to BUY 1000 shares of Stock X at INR 3.5 per share and the other side of the column indicates an order to SELL 2000 shares of Stock X at INR 4 per share. The other serial numbers represent similar such orders for the same stock placed by other traders. The Matching engine of the Stock Exchange matches the Correct BUY with the correct SELL based on PRICE-TIME priority rule.

Data

For the purpose of this study LIMIT ORDER BOOK's historical data was obtained from BSE for the period of January 2020. Since the Limit Order Book contains data in the time granularity of milliseconds i.e. The LOB data comprises of 32 Giga Byte size comprising of 36 lakh data points in one trading day. Therefore inorder to enable data processing LOB of 1 month (January 2020) was considered.

This month had 23 Trading days. HENDERSHOTT et al., 2011, p. xx) consider a data set from Deutsche Bourse for a period of 5 years. On the other side Hendershott and Riordian (2013) in another study consider a time frame of 13 days of a dataset of 30 stocks from the Deutsche Bourse. Although many authors have explored "Month-of the-year" anomalies, these anomalies are dependent on portfolio and expected returns. Since this study aims to examine the Order Placement pattern of Algorithmic Traders and Non Algorithmic traders, it is assumed that month of the year is indifferent to a trader.

The data set comprises LOB data for 9 stocks. The orders are divided into Market sessions starting from 9.00 AM IST to 9.30 AM IST (30 minutes) and 14.45 PM IST to 15:15 PM IST (30 minutes) The BSE classifies these sessions as Pre –Open session, Continuous session and Closing session. Since one of the research objectives is to examine Session timings as a variable of Trade behavior, data for only these sessions have been considered.

The 23 days trading data is segregated into 23 folders. Each folder comprises the LOB data for the 9 stocks for the above mentioned session time. The number of observed data points or orders will be approximately 36 lakh orders for 1 single day. For instance assuming there is a Limit

Order entering the server every millisecond, the number of orders from 9.00 AM- 9.30 AM trading day would be 6* 10^4* 30minutes which is 18 lakh orders in one folder (representing one day) .Parsing 36 lakh data points of each day for 23 days complicated the analyses of the data. The 9 stocks considered for this study are based on Market Capitalization of a Stock. The Market Capitalization as on ***** date has been considered inorder to select the stocks.

Market Capitalization (INR) = Total number of free floating equity shares * Market price of the share on a particular day.

Below are the 9 stocks along with the SCRIP CODE of BSE

Table 1.3 Selected stocks and scrip codes in BSE

LARGE CAP STOCKS		
SECURITY ID	SECURITY CODE	SCRIP
RELIANCE	500325	RELIANCE INDUSTRIES LTD.
TCS	532540	TATA CONSULTANCY SERVICES LTD.
HDFCBANK	500180	HDFC BANK LTD.
MID CAP STOCKS		
SECURITY ID	SECURITY CODE	SCRIP
MRF	500290	MRF LTD.
BEL	500049	BHARAT ELECTRONICS LTD.
IGL	532514	INDRAPRASTHA GAS LTD.
SMALL CAP STOCKS		
SECURITY ID	SECURITY CODE	SCRIP
TTKPRESTIG	517506	TTK PRESTIGE LTD.
NATIONALUM	532234	NATIONAL ALUMINIUM CO.LTD.
SYNDIBANK	532276	SYNDICATE BANK

The data set consists of 13 variables which are as below with description:

Table 1.4 Description of variables in the LOB

Trading Session	It indicates the trading session of the Stock market namely Pre-Trading, Order Entry, Continuous Trading and Closing of trading.
Scrip Code	Designated Number given by BSE for each stock

BuySell	Indicates whether the Order was to Buy a stock or Sell
Order Type	It represents whether the order was a Limit order or Market Order
Rate	Price of a Stock expressed in paise at which order is entered (For BUY or SELL)
Quantity	Quantity or Volume of Stocks being bought or sold
Available Quantity	Indicates the actual quantity a trader wishes to purchase. This is usually not revealed by the Exchange
Order Time	Time Stamp for every order (milliseconds)
AUD Code	A- Addition. U-Updation and D-Deletion of an order
Order ID	Unique reference number for every Order submitted into the LOB
Algo Flag	N- Order is from a Non Algorithmic Trader Y- Order is from an Algorithmic Trader

Research questions RQ1 and RQ2 have been attempted through literature review. Academic literature from Year 2006 onwards has been considered in order to understand the evolution and development of Algorithmic Trading. Since Algorithmic Trading was at its nascence; articles prior 2010 is necessary. The key words used were Algorithmic Trading, Algo Trading and HFT

Similarly to understand Impact studies of Algorithmic Trading on Liquidity, Volatility and Price Discovery, year of publishing has not been considered since the Impact study articles are thin. The key words used were Algorithmic Trading and Liquidity, Volatility, Price discovery, Market efficiency and HFT.

Since it is assumed in this study through literature review that there is a significant dissimilarity in the order placement (Orders added and deleted) behavior as well as the capacity in using computational power by Algorithmic and Non algorithmic traders, this study aims to test the argument by measuring relevant variables. Therefore a deductive form of reasoning is adopted

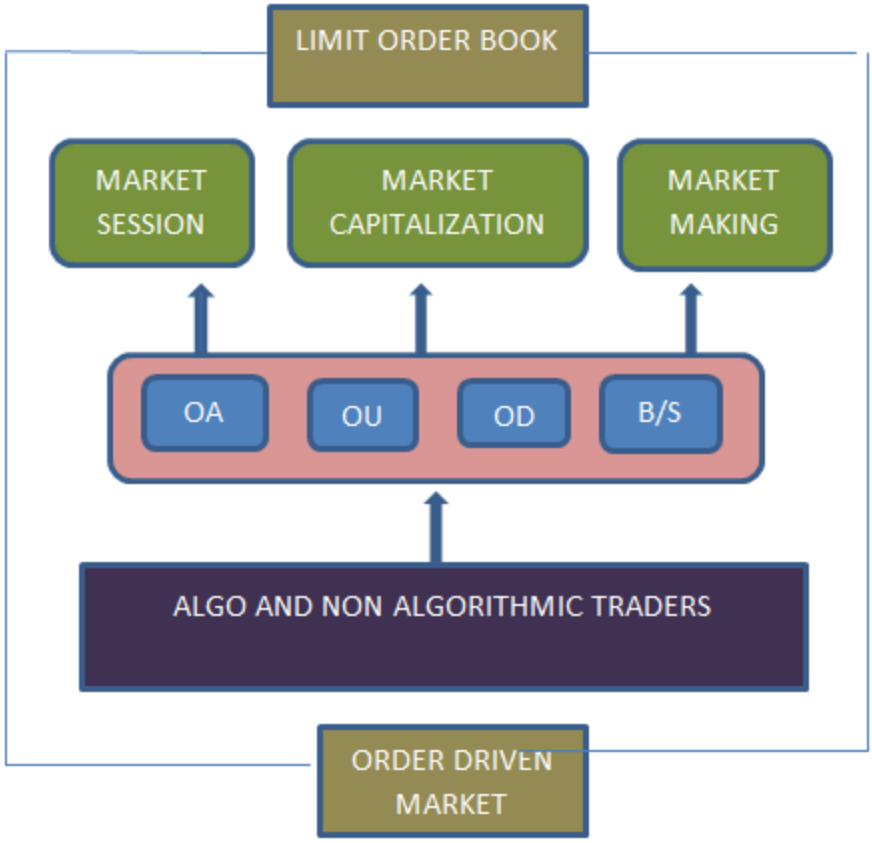
for this study. Since the study requires analyzing numerical data, a quantitative research method is adopted to address RQ3 and RQ4.

From the extant research it can be construed that the two market participants (AT and NAT) interact in the same market but exhibit trading behavior some of which are similar and dissimilar. The above literature suggest that there is a significant dissimilarity in the order placement (Orders added and deleted) behavior as well as the capacity in using computational power. Therefore this study aims to take these studies further by exploring dissimilarities in trading behavior based on variables which are not obvious.

Conceptual Framework

The framework visually represents the interaction of AT and NAT. The study aims to find out the interaction based on Market Session, Market Capitalization and Market Making. These variables are investigated using a proxy variable since there are no direct measurements in the Limit Order Book to understand the AT and NAT behavior. The proxy variables are Order placement represented by OA- Order Addition, OU- Order Updation and OD-Order Deletion and B/S- BID/ASK quotes. This study is between participants who trade in an Order driven Market where in the quotes/orders placed by every market participant is visible to the other participant. Also the order flow details which are studied here are Limit Orders that accumulate and rest in the Limit Order Book till matched.

Fig.1.5 Conceptual framework



OA- Order Addition, OU- Order Updation, OD-Order Deletion, B/S –Bid Ask

Rationale for the selection of variables for examining market interaction

The Stock market provides ample opportunity for every participant to trade and thrive. There are different participants with similar motive which is to register profits. But the dissimilarities amongst participants can be observed in conception of trading strategy, execution of the trading strategy and market timing. Therefore For the purpose of this study we intend to examine trading activity in general and the convergence and divergence of Algorithmic and Non-algorithmic traders by analyzing the following variables

- Market Capitalization
- Session timings
- BID and SELL quotes

- Order Modification denoted by AUD Code

Market Capitalization of a stock (Freefloating shares * Market Price of the share) determines the relative strength in terms of Trading volume, Liquidity, Daily turnover in the Stock market. But it is not established whether Algorithmic or Non Algorithmic traders accord significance to Market Capitalization while formulating a strategy. Similarly Market session timings is a crucial factor while trading since both the participants gauge the depth and pulse of the Stock market at frequent intervals of time. Therefore this variable requires examination if there is any statistical significance between participants and market session timings. Every Stock market has a bespoken role of providing liquidity. Although there are designated market players known as Market makers in a QUOTE driven market, there is no such de-facto Market maker in an ORDER driven market. But the existence of market making behavior by either of the AT or NAT is yet to be explored. This is important from regulatory perspective as well since the Stock market regulators can identify if the very high order frequency is a Market making effort or only an intention to flood the Order Book.

OBJECTIVES AND HYPOTHESIS FORMULATION

After the literature review and based on the identified research gaps following objectives are proposed as a part of this study;

1. To examine trading activity of AT and NAT based on market capitalization
2. To examine trading activity of AT and NAT based on market session timings
3. To examine market making behavior by AT and NAT

Formulation of hypotheses

Provision of liquidity is one of the frequently identified research findings on algorithmic trading. (Scholtus et al., 2014) used trade data of highly liquid stocks to understand the order placement pattern of AT. This indicates that while considering the data set, authors have considered liquid stocks which have high trading activity irrespective of AT activity. Brogaard (2010) examined

the impact of HFT on equity market. According to him HFT based trading is more dominant than human based trading. HFTs trade in large volume stocks, and they reduce trading as volatility increases. In this research the author indicates that HFTs trade in high volume stock. Therefore it can be surmised that AT activity positively improves the liquidity of those stocks which are already liquid. This research aims to examine the trading activity of AT and NAT based on stocks which are less liquid. Also it requires to be understood if the liquidity and volatility are experienced throughout the trading day or only at certain points of time. Here liquidity of a stock is represented by market capitalization and the following hypothesis is constructed:

H0: There is no statistically significant difference between Order status of AT and NAT and Market capitalization

H1: There is statistically significant difference between Order status of AT and NAT and Market capitalization

Similarly following hypothesis is constructed to examine AT and NAT activity based on session timings:

H0: There is no statistically significant difference between Order status of AT and NAT and session timings

H1: There is statistically significant difference between Order status of AT and NAT and session timings

(Matsunaga & Kita, n.d.) in their research paper explain the process of Market making in a Quote driven market. The authors opine that in this method of market-making, the specialist Market maker is the only source of supplier of liquidity in the market resulting in a dominant position in a trade. (Chakraborty & Kearns, 2011, p. xx) in their research add another dimension to market making in a quote driven market. Here Market-makers use computer based algorithms to earn a profit- SPREAD. The hypothesis constructed to examine AT in a market making ability is as follows:

H0: There is no market making activity visible in the market by AT and NAT

H1: There is market making activity visible in the market by AT and NAT

ANALYSIS AND FINDINGS

Objective 1:

A non- parametric association test was run to test the statistical significance between Order status and Algo/Non Algo activity. A Chi-Square test of independence was performed to examine the association between Order placed by A and NA and Market Capitalization.

algo_flag	N	Y
capitalisation		
L	143620	94667533
M	26370	7364459
S	13458	2959953

Algo Flag Vs Capitalization

---

c: 30199.67104294803
p: 0.0
dof: 2
expected: [[1.65370586e+05 1.28911598e+04 5.18625399e+03]
[9.46457824e+07 7.37793784e+06 2.96822475e+06]]

A chi-square test of independence shows that there is a statistically significant difference in order placement by Algo and Non Algo traders in L, M and S stocks, *X-squared = 30199.67104294803, df = 2, p-value < 0.00000000000000022.*

Thus the Null Hypothesis being rejected it may be surmised that there is a statistically significant difference and Algotraders and Non Algotraders demonstrate trading behavior with regard to Market capitalization.

Algo Trade Intensity Measure

Agarwal and Thomas (2014) introduce AT Intensity measure which reports the percentage of algo trades as a percentage of total trades in a given time interval. The formula is used is

$$AT(i,t) = TTVAT(i,t)/TTV(i,t)*100;$$

We propose a minor modification to the measure that incorporates decomposability, a desirable mathematical property for an aggregate measure, and also a defined range for easy interpretation of the intensity measure. The new measure, ATn can be written as

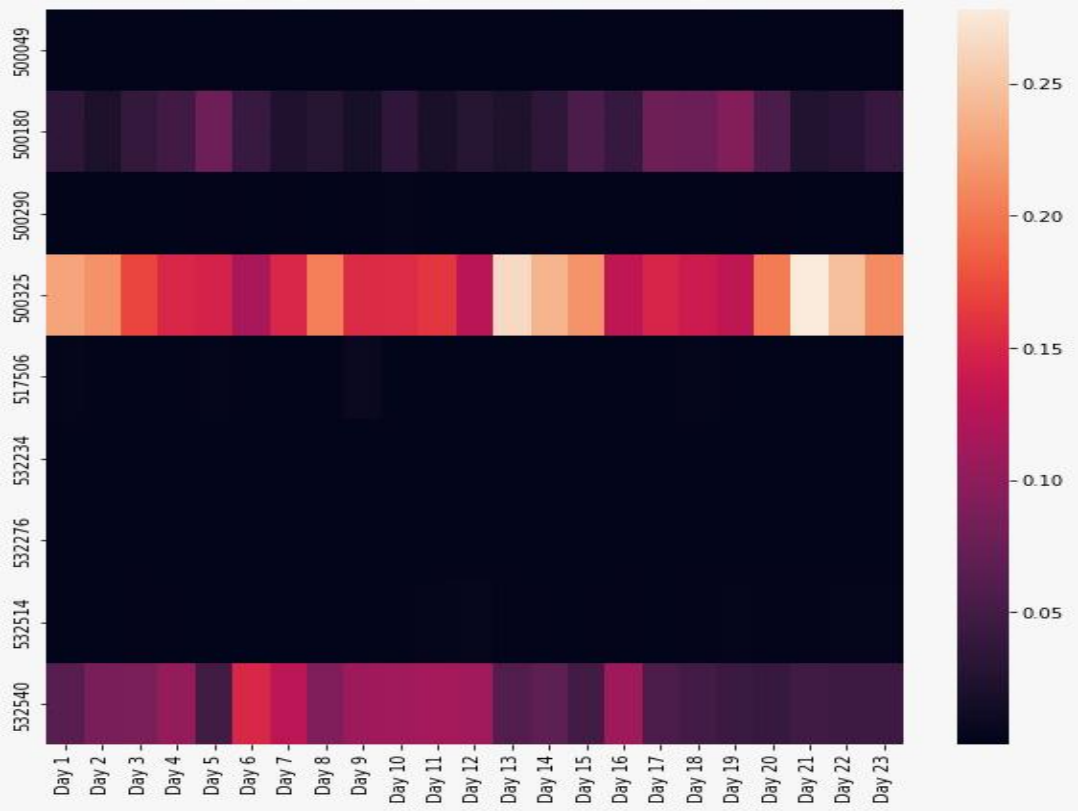
$$ATn = Abs\left(\frac{TTVAT(i,t)-TTVNAT(i,t)}{TTVAT(i,t)+TTVNAT(i,t)}\right)$$

Here the TTVAT(i,t) refers to total traded value of algo trades during time t in stock i, and TTVNAT(i,t) refers to total traded value of non-algo trades during time t in stock i

The advantage of this measure is that compared to the earlier measure, this is decomposable, and that it can bring the AT intensity measure in a (0,1) interval where values closer to zero indicate low intensity and values closer to one will indicated high intensity. One can bring in an aggregate measure for algo trade intensity for the market as a whole by modifying the Atn by adding the required number of summation operators. For instance if one wishes to capture the trading intensity for all stocks in a given time period then the new measure can be re written as

$$\sum_{i=1}^{n} Abs\left(\frac{TTVAT(i,t)-TTVNAT(i,t)}{TTVAT(i,t)+TTVNAT(i,t)}\right) * \frac{1}{n}$$

Fig.1.6 Heat map showing Algorithmic Intensity



The above heat map represents the Algotrading Intensity on all the 23 days for the selected 9 stocks. It can be observed that SCRIP number 500325- RELIANCE INDUSTRIES LTD. shows very high AT intensity on most of the days. Similarly SCRIP number 532540- TCS LTD. also shows high AT intensity. SCRIP number 500180- HDFC BANK LTD too has AT intensity on few days. All these 3 scrips are LARGE MARKET CAPITALIZATION stocks. Rest other 6 stocks belonging to Medium and Small Capitalization segment hardly show any AT intensity.

Thus it may be concluded that there is a statistically significant behaviour between AT and NAT based on trading in Market Capitalization. With AT trading almost 91% of trades in Large Cap and NAT trading almost 78% it can be concluded that Small cap and Medium Cap are not receiving very high trading and AT activity.

OBJECTIVE 2:

A non- parametric association test was run to test the statistical significance between Order status and Session timings. A Chi-Square test of independence was performed to examine the association between Order placed by AT and NAT and Market Session timings

minute	1	2	3	4	...	57	58	59	60
algo_flag					...				
N	21675	1739	1748	2110	...	1760	1312	801	211
Y	0	0	0	0	...	1570347	1082504	660526	158489

[2 rows x 60 columns]

0----------

second	1	2	3	4	5	...	3129	3130	3131	3132	3133
algo_flag						...					
N	4193	783	741	462	378	...	0	3	2	1	4
Y	0	0	0	0	0	...	2866	2808	3284	3628	4235

minute	1	2	3	4	...	57	58	59	60
audcode					...				
A	21483	1506	1538	1887	...	50950	35344	19801	3084
D	183	181	151	153	...	48025	32373	18250	2742
M	0	0	0	0	...	1151	1218	452	56
U	9	52	59	70	...	1471981	1014881	622824	152818

Order Status & Session timings

Association between Time in Minutes with AUDCODE

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c: 1436318.9363472247
p: 0.0
dof: 177

A chi-square test of independence shows that there is a statistically significant difference in order placement by Algo and Non Algo traders during various market sessions., *X-squared* =1436318.9363472247, *df = 177*, *p-value < 0.00000000000000022.*

Thus the Null Hypothesis being rejected it may be surmised that there is a statistically significant difference in Order placement and Market session timings of Algotraders and Non Algotraders.

.

OBJECTIVE 3:

A market maker is a participant who provides BUY quote order as well as SELL quote order to a Stock. A market maker provides liquidity to a commodity. The market maker performs the function of an intermediary by buying from and selling to respective counter parties in a stock market. It can be inferred that a Market Maker transacts on both sides of the market; Buy side and the sell side of the market and convey their intention in the form of QUOTE.

The literature does not provide a metrics or a measure to identify the Market Making activity of the participants. Therefore this study has developed a metrics to identify which can be the second contribution to the body of knowledge. The measurement used to measure MM ability is OTR- Order to Trade Ratio (OTR)

Order to Trade ratio means the Total number of Orders received by the Server over the Number of Orders actually filled.

Market making measure

$$OTR = TAUD_{(i,t)} \div TTE_{(i,t)}$$

$$\text{i.e} \quad OTR_{(i,t)} = \frac{TOA_{(i,t)} + TOU_{(i,t)} + TOD_{(i,t)}}{TTE_{(i,t)}}$$

TAUDO IS TOTAL ADDED UPDATED DELETED ORDERS. **TTO** stands for Total Traded Orders. The first formula is a composition of **TOA** (Total Orders Added), **TOU** (Total Orders Updated), **TOD** (Total Orders Deleted) for Security I at a point of time of 't'. **TTO** stands for Total Trades Executed for Security I at point 't'

Table 1.5 OTR based on each trading day in the LOB

DATE	TTE	TAUDO	OTR
1-Jan	18942	2666233	140.7577
2-Jan	29049	2922371	100.6014
3-Jan	30500	4453755	146.0248
6-Jan	38375	4827989	125.8108
7-Jan	34287	4743255	138.3397

8-Jan	27690	5774815	208.5524
9-Jan	35162	4006206	113.9357
10-Jan	27053	3785077	139.9134
13-Jan	24415	3684208	150.8994
14-Jan	26358	4378405	166.1129
15-Jan	31168	4551837	146.042
16-Jan	33513	4072344	121.5154
17-Jan	36535	6743401	184.5737
20-Jan	53433	10053693	188.1551
21-Jan	30706	4631460	150.8324
22-Jan	27860	3940452	141.4376
23-Jan	30283	4028295	133.0217
24-Jan	31035	3790473	122.1354
27-Jan	39354	3757478	95.47893
28-Jan	41342	5331823	128.9687
29-Jan	37960	4221996	111.2222
30-Jan	39475	4161286	105.4157
31-Jan	48097	4465093	92.83517
	772592	**104991945**	**135.8957**

Total Trades Executed	772592
Total AUDM	104991945
Deleted Algo Orders	3329543
Deleted Non Algo Orders	20603
TAOT	135.89572
DAOTT	4.6449096
DNAOTT	0.0266674
DAOTT/ DNAOTT	174.17949

The above Table offers a glimpse of the total data analyzed for all companies under study for the entire period of study. We can see that the Total Trades Executed (TTE) is only a fraction of the TAUDO received by the exchange. The measure DAOT and DNAOT stands for Deleted Algo Orders to Total Trades Executed (TTE) and Deleted Non Algo Orders to Total Trades Executed (TTE) A value higher than 0 indicate that not all orders that were placed by the trader (be it Algo or Non-Algo) resulted in a trade. Since each order while getting placed will have an impact on the total volume available in the market at that specific time and price level, once the order gets

deleted the price level changes, and hence we focus specifically on the deleted orders to total trades executed ratio. As can be seen the number of Deleted Orders to Trades Executed by Algo traders is 4.64 indicating that if a total of 1000 trades gets executed then almost 4640 orders are cancelled by the Algo traders. This is number is extremely low for the Non-Algo traders where for every 1000 orders that get executed only 26 orders are cancelled by the Non-Algo traders. Now if one were to take a ratio of DAOTT and DNAOTT we can see that Algo traders cancel 174 times more orders than a Non-algo trader. The measure DAOTT/ DNAOTT gives us an idea about the impact of Algo Traders on Non-Algo traders. The large number of Deleted Orders indicates that a large number of Orders are not getting converted to execution leading us to believe the Orders are placed only to clog the server with no intention of market making. On the other side the Non Algo Traders have very less room for demonstrating market making ability with the dominance of Algo traders. Thus we fail to reject the null hypothesis and it may be concluded that market making is not visible in the market by AT and NAT.

FINDINGS AND DISCUSSIONS

A stock market provides ample opportunity for every market participant to derive profits depending on trading capital and trading strategies. Although the market is sometimes asymmetric regarding information, no market participant can beat the market always. But with the introduction of algorithmic trading, a new breed of market participant emerged which possess distinct features threatening the very existence of other market participants. With markets becoming heterogeneous compounded by asymmetric information, it necessitates research on understanding the trading behavior of these two types of market participants, namely algorithmic traders (AT) and non-algorithmic traders (NAT). The discussions here flow in the order of the research questions indicated earlier.

Seminal research in the area of algorithmic trading emerged around 2008. All the authors embrace a common meaning of algorithmic trade. These traders are largely institutional traders who undertake proprietary trading. However most of these studies that emerged in 2008 spanning to 2011, identified the characteristics of AT through a proxy based on speed of order entry into the exchange's server. However later are able to identify an algorithmic trade since many stock exchanges by then had a provision to identify algorithmic orders and also assign unique identification number. This study is able to contribute another dimension about AT especially in the Indian market. The AT activity similar to NAT is determinant to Trade session timing and market capitalization.

Based on the review of literature and the impact studies following findings can be surmised:

- Several academic literature conclude that there is an impact of AT on liquidity, volatility and price discovery. But these studies are based on the historical trade and order book data. Research conducted in a simulated environment contradicts the findings of impact studies. As more Algorithmic traders' participation increases in a trading day, liquidity increases but after reaching a certain threshold limit, the benefit are already exhausted suggesting that Algorithmic Trading activity may not improve liquidity perennially.
- Similarly an observation based on NAT and AT contribution indicates that NATs contribute more to volatile market. The reason that can be attributed to AT reducing volatility might be due to the presence of HFT algorithms. HFT traders are able to trade

based on Nano second time granularity and also they are able to slice a single order into multiple orders which are placed at high frequency. HFTs cannot thrive if market is highly volatile because their impact cost increases if the Price spread maximizes.

- Algorithmic traders are Rule-based traders also called as System traders. Algorithmic traders possess extreme speed in Order placement, Order modification and Order placement. The Algorithmic traders trade in multiple markets to exploit the advantage of Arbitrage opportunities. With Colocation facility which enables the concerned Algorithmic trader's to place server close to the Stock exchange's server; has enabled them to obtain information with minimal latency. Colocation facility in India too has contributed to increase AT activity.
- Another dimension was the impact of Algorithmic Trading on price discovery. Research also focuses on AT impact on market efficiency. The ability to incorporate new information into prices is known as Price Discovery in a Stock market. There is no conclusive opinion about the impact of AT on price discovery. Although few researchers assert that markets have become more efficient but there is also skepticism that markets are not level playing field anymore since ATs have the capacity to respond to information very fast and exploit the opportunity.
- Simulated experimental research examining the interaction between Systems based trader and human based trader has concluded there exists significant difference between both. Our study too asserts that AT and NAT have dissimilarity in trading. The research conducted as a part of this study contributes to further knowledge about trading behavior of AT and NAT especially based on stock market's session timing. Further it was found that the Pre-opening session i.e from 9 AM- 9.15AM of the trading day is dominated by NAT Traders whereas the continuous session i.e from 9.30 AM to 3.30PM the AT activity overtakes NAT activity. A chi-square test of independence shows that there is a statistically significant difference in order placement by AT and NAT during various market sessions. Thus observing trading behavior based on session timings offers insight about trading psychology. Also it can further enable market regulators to monitor fleeting orders and also indicate that particular session timing when trading volumes surges.

- It is found that the Large Capitalization stocks receive comparatively more Order updations compared to Small capitalization stocks. There is a statistically significant difference in AT activity in Large Capitalization and Small capitalized stocks. ATs and NATs demonstrate trading behavior with regard to Market capitalization. Besides liquidity provision it is also important to study if Algorithmic activity is sufficiently visible in Mid-capitalization and Small- capitalization stocks or is it the NAT who are the active market participant in these stocks. This would further hint market authorities if AT activity should be promoted especially for Mid cap and Small Cap stocks to increase trading volume. At present in India's Stock Exchange there is a separate listing for Small Cap stocks and also a trading ring in the OTC market. If AT activity can provide liquidity for Small and Mid Cap stocks, then the stock market activity is likely to change. Another contribution of this research is in developing a better way of measuring AT activity intensity. Agarwal and Thomas (2014) introduce AT Intensity measure which reports the percentage of algo trades as a percentage of total trades in a given time interval. There is no available research that examines the association between market capitalization of stocks and AT/ NAT activity. Stocks that have large market capitalization (INR20,000 Crore or more) are proven to be highly liquid stocks. Volatility observed in such stocks is low.
- Examining trading behavior in an order-driven market is essential to understand if AT and NAT assume the role of an undesignated market maker. Especially with ATs ability to demand and supply liquidity, it is considered necessary in this study to measure market making ability of ATs. This is another contribution of our research since no academic literature has developed a measurement for observing market making. Research suggests that ATs flee the market as soon as there is an adverse news. We have used the Order to Trade Ratio as a measure to examine the market making ability. Order to Trade ratio means the Total number of Orders received by the server over the number of orders actually filled. The number of Deleted Orders to Trades Executed by AT is significantly more than the NAT. This ratio is extremely low for NAT where for every 1000 orders that get executed only 26 orders are cancelled by them. Now if one were to take a ratio of ATs we can see that ATs cancel 174 times more orders than a NAT. The large number of Deleted Orders indicates that a large number of Orders are not getting converted to

execution leading us to believe the Orders are placed only to clog the server with no intention of market making. On the other side the NAT have very less room for demonstrating market making ability with the dominance of AT. The SEBI already has a high OTR as a penalty to discourage ATs from unnecessarily placing large orders which do not get executed. Our findings confirm SEBI's concern. Since a large number of orders do not rest in the Limit Order Book it can be seen that ATs create a pseudo picture of Order placement.

- With AT activity intensifying in the Indian bourses ; the concerns are emerging about the relevance of NAT. Luca (2011), indicated that there is a significant difference between an Algorithm and Human trading behavior where in it is the human trader's strategic thinking that distinguishes them. The experiments reveal that humans demonstrate an upper hand in terms of strategy formulation and spontaneity in reacting to sudden market aberrations. Also the ability of the Algorithmic Trader to alter BID/ASK quotes and assuming a role of a market maker in an Order-driven market leaves scope for further exploring. By looking at the measures computed to see the impact of algo traders in total market activity, we find that AT , armed with computing speed and faster reaction to news, are able to drive the market structure leaving the NAT at a disadvantage. It can be opined that in the coming future the stock market activity might witness a near 100% presence. This leaves room to understand if Human Traders may be rendered ineffective. Also since the execution cost of an order by an Algorithm is cheaper, many Institutions may adopt Algorithmic trading. This also may lead to a 'No- incentive' situation for a NAT leaving a question of does AT create a level playing field for all?

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Sender Name	SHUBHASHREE ACHARYA
From Account	XXXX XXXX XXXX 2691
Beneficiary Name	CHRIST UNIVERSITY
Account Number	A144A1101610071
Amount	₹ 49,000
Remarks	Phd Fees for 2019 year
Transaction ID	2022010637036877
Reference ID	200612993891
Transaction Date	06/01/2022 | 12:30 PM
Transaction Status	Successful

Transaction Receipt

Sender Name	SHUBHASHREE ACHARYA
From Account	XXXX XXXX XXXX 2691
Beneficiary Name	CHRIST UNIVERSITY TRUST
Account Number	A379A1101610071
Amount	₹ 21,000
Remarks	Phd fees for 2019
Transaction ID	2022010637037118
Reference ID	200612995854
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